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Rejecting Rational Expectations in Panel Data: Some New Evidence

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Rejecting Rational Expectations in Panel Data: Some New Evidence*

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Abstract:

Early empirical tests for rationality in survey expectation data have either used summary data and thus neglected the resulting aggregation bias or used individual data but ignored the likely correlation of forecasts due to the same aggregate shock surprising economic agents. Two recent papers took these problems into account and arrived at exactly opposite conclusions: One rejected the Rational Expectation Hypothesis, the other did not. This paper adds evidence from a new data set which features three advantages none of the previously used data sets could combine: (a) Names of forecasters are given along with the forecasts so that they have an incentive to do as well as possible; (b) forecasters predict a quoted price so that there is no ambiguity as to what they are trying to forecast; (c) forecasts for the same target period are made at different points in time so that alternative implications of the Rational Expectation Hypothesis can be tested. Three different tests are employed in this paper. They all reject the Rational Expectation Hypothesis.

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0. INTRODUCTION

Rationality of survey expectation data has been tested before. However, earlier papers either used summary measures such as the mean forecasts which are systematically biased (see Appendix 1) or they pooled data neglecting the likely correlation of forecast errors across agents.[1] Two recent papers took care of these problems and, furthermore, used the panel data to look at idiosyncratic components in expectations -- components that are not consistent with the conventional Rational Expectations Hypothesis. Their evidence is mixed: Ito [1990], studying US-$/Yen exchange rate expectations, rejected rationality of expectations for his data set. Conversely, Keane/Runkle [1990] did not reject rationality in expectations of the U.S. GNP deflator.

This paper adds evidence from a new data set, compiled from a commercial newsletter. The data has three features that previously used data could not combine: (1) Names of the forecasters are published along the forecasts so that there is a strong incentive to give the best; (2) The forecast variable is an interest rate so that none of the ambiguities possible with national accounting data can arise; (3) Forecasts of the same target period are given at different points in time so that alternative implications of the Rational Expectations Hypothesis, not previously considered, can be tested.

In section 1 of this paper, the data set used is described. Section 2 discusses econometric issues and section 3 presents the results of conventional tests for unbiasedness. The data used has drawbacks in that the relatively short time horizon does not allow proper analysis of the time series properties. The expectation variable and the corresponding realization series both seem non-stationary, though co-integrated. The tests for unbiasedness in section 3 involve level

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[1]Papers in the first group include Pesando [1975], Carlson [1977], and Pearce [1979]. A paper in the second group is Figlewski/Wachtel [1981].

regressions whose results must be taken with care. On the other hand, when testing for efficiency, the Rational Expectations Hypothesis leads to alternative regression specifications that imply under the null hypothesis stationarity of both the regressand and the regressors. Section 4 reports the results of a first series of such regressions, testing for the presence of idiosyncratic forecast errors. Section 5 extends the analysis, testing for the efficient use of various information variables available when expectations were formed.

The usefulness of published survey data to test for rationality in expectations has also been questioned on different grounds. After all, we do not know whether survey participants act upon their predictions in the market place, or, whether their public announcements are the result of some private optimization problem other than minimizing the the expected forecast error. Section 6 reports the results of a regression equation which is derived from the idea that survey participants when announcing a public forecast might want to trade off the size of their revisions from past announcements for truthfulness in their new, but unreported expectations. They might make predictions which they know are not optimal because they are (perhaps rationally) unwilling to admit they were wrong.

The tests in sections 3, 4 and 5 of this paper reject the Rational Expectation Hypothesis. In particular the results in the first two of these sections gain strength as they have only used implications of the Rational Expectation Hypothesis that do not require any specification of the model the survey participant might have had in mind. The results in section 6, in turn, support the general case for analyzing survey expectations. Had the participants been found not to admit that they were wrong in previous forecasts, then the validity of the data for further use should have been questioned. Section 7 summarizes the results.

1. The Data

The expectation data used for the empirical work in this paper comes from the North-Holland *Economic Forecasts* publication. This monthly newsletter publishes forecasts of key economic variables for 23 industrialized or industrializing countries. However, only the U.S. data is sufficiently rich for the purpose of this work since it can be viewed as a small panel of expectations. The data are not summarized. Individual forecasts are given along with the name of the forecaster. There is thus an incentive to try to forecast as precisely as possible.

For the U.S., some 30 professional forecasters or institutions report their forecasts at the beginning of each month to the North American editorial board. The editors of the newsletter provide the forecasters with the latest data. When the forecasts are made, the past month' government publications such as the *Survey of Current Business* of the U.S. Department of Commerce are available. I dated the time when the forecasts were made according to this availability of information. The variable definitions generally coincide with those of the official statistics.[2] For the empirical work, only forecasts of those participants who reported at least 15 times over the sample period from December 1984 to June 1990 were used. The cross-section dimension of the data was thus reduced to N=23. The average number of non-missing observations per participant is 18.

The expectation variable used is the forecast of the annualized discount rate on new issues of 91-day Treasury bills, based on weekly auction average rates. As all other forecasts in the newsletter, this rate is predicted for the quarters of the calender year. The corresponding realization data needed to be compiled and comes from the *Federal Reserve Bulletin*. It is calculated as a simple average of

[2] All details in letter from Professor Victor Zarnowitz, North American editorial board, to the author.

monthly data which is in turn computed from the average weekly auction rate already quoted on annualized discount basis. Comparison with the auction data published in the press did not reveal any inconsistencies.

[About here Table 1 -- Results of a weekly auction of T-Bills]

The forecast data was split into three, small homgeneous panels of first month, second month, and third month forecasts resp. which give a sample size of T=22 for the first two months, and of T=23 for the third-month-of-the-quarter forecasts resp. In this paper, only current and one-quarter-ahead forecasts have been used. The interest rate forecast data was chosen because it predicts a quoted price and thus some of the ambiguities that could arise when predicting national accounting data are excluded. In the U.S., e.g., the Commerce Department revises its most recent data releases for two consecutive months and then again every year in July. The results of tests for rationality in Keane/Runkle, e.g., depend crucially on which realization data is used. In their paper, survey forecasts are rational expectations of the early 45-day announcements of the GNP deflator made by the U.S. Commerce, but not of the revised data, released in July of each year by the same government agency.

[Here Figures 1-4 -- Average Forecasts and Average Forecast Errors]

2. Econometric Issues

In its most general form, the Rational Expectations Hypothesis states that economic agents' subjective probability distribution is identical to the objective probability distribution of the model thought to be generating the variable at hand. Assuming a quadratic loss function, statistical theory then implies that the conditional mathematical expectations is the optimal prediction of the variable of interest.[3] Derived for optimizing agents with a quadratic loss function, Rational Expectations must be unbiased, with serially uncorrelated forecast errors, orthogonal to any information known when the forecast was made. Tests of rationality involve these two implications in one or the other form.

The following two regressions would test for unbiasedness and efficiency, respectively:

$$X_t = \beta_0 + \beta_1 X_t^{e,t-1} + u_t \tag{1}$$

$$(X_t - X_t^{e,t-1}) = I_{t-1}\, \mathbf{d} + v_t \tag{2}$$

where X_t is the realized value of any variable of interest in time t, $X_t^{e,t-1}$ denotes the prediction of that variable for period t made at t-1, I_{t-1} is the information set available at time t-1, **d** is a vector of coefficients, and u_t and v_t are n.i.i.d error terms with zero mean and variance σ_u^2 and σ_v^2 resp.

Unbiased expectations in equation (1) should yield estimates which do not reject the joint hypothesis H_0: $[\beta_0,\beta_1]' = [0,1]'$. This is a weak test of rationality because it only requires that the forecast error be uncorrelated with the forecast. Equation (2) constitutes a stronger test of rationality, hypothesizing that all elements of **d** should be zero. Non-zero elements would imply inefficient use of available

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[3]See Appendix 2 for the derivation of this result. As a matter of fact, for the conditional expectation to be the optimal predictor, the loss function need not be quadratic. As one set of conditions, it is sufficient if the loss function is symmetric about the forecast error, if it is differentiable almost everywhere and strictly monotonically increasing on the whole range from $-\infty$ < error < ∞, and if the conditional probability density function of X is symmetric about the conditional mean. See Granger/Newbold [1986].

information.

Note, first, that rejection of unbiasedness would not imply irrationality if we left the linear world and if forecasters had, for example, an underlying asymmetric loss function. Second, testing for unbiasedness does not require specification of the model used by the forecasters nor particular assumptions on the information set. Conversely, testing for the efficient use of available information requires a priori judgement because agents among each other (and those who test for their rationality) might not agree about what constitutes the "relevant" information set.

When implementing tests as outlined, two econometric problems arise that have been ignored in the early empirical literature on survey expectations. First, with overlapping forecast horizons, economic agents will not have knowledge of all previous forecast errors when making the next forecast; and, if they stick to some forecast rule for more than one period, the forecast errors will be serially correlated. Second, forecast errors across agents are likely to be correlated because they are due to the same aggregate shock hitting the economy. While OLS estimates in these cases are still unbiased, the variance/covariance estimates of the regression coefficients could be downward biased if there was positive error correlation. Downward biased variance/covariances estimates could lead to erroneous rejection of the null hypothesis.

3. Testing For Unbiasedness

The tests reported in this section are on the unbiasedness of the forecasts. All individual forecasts were used. This increases the power of the regression and avoids any aggregation bias. Using summary measures such as the mean forecast would ignore two potential sources for an aggregation bias. First, the mean of many individual forecasts, each conditional on a private information set, is not itself a rational forecast conditional on any particular information set. Second, aggregation might mask systematic idiosyncracies which might cancel each other at the aggregate level.

The data was organized per time period first. Let

$$\mathbf{y}_t = \begin{bmatrix} Y_{1t} \\ \vdots \\ Y_{Nt} \end{bmatrix}, \qquad \mathbf{X}_t = \begin{bmatrix} 1 & X_{1t} \\ \vdots & \vdots \\ 1 & X_{Nt} \end{bmatrix}, \qquad \mathbf{u}_t = \begin{bmatrix} u_{1t} \\ \vdots \\ u_{Nt} \end{bmatrix}$$

and $$\mathbf{b} = \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix}$$

where $\mathbf{y}_t$ is a (Nx1) vector of one period realizations, $\mathbf{X}_t$ is a (Nx2) matrix with the X_{it} being the individual forecasts, $\mathbf{b}$ is a (2x1) vector, and $\mathbf{u}_t$ is (Nx1) again. The data can then be stacked along time to form:

$$\mathbf{y} = \begin{bmatrix} \mathbf{y}_1 \\ \vdots \\ \mathbf{y}_T \end{bmatrix}, \qquad \mathbf{X} = \begin{bmatrix} \mathbf{X}_1 \\ \vdots \\ \mathbf{X}_T \end{bmatrix}, \qquad \mathbf{u} = \begin{bmatrix} \mathbf{u}_1 \\ \vdots \\ \mathbf{u}_T \end{bmatrix}$$

The pooled regression is then:

$$\mathbf{y} = \mathbf{X}\,\mathbf{b} + \mathbf{u} \tag{3}$$

where **y** is now a (TNx1) vector, **X** is a (TNx2) matrix , **b** is a (2x1) vector, and **u** is the (TNx1) vector of disturbances.

Under the Null hypothesis of unbiased rational expectations, the intercept and slope coefficient in **b** are common for all i, t, namely 0 and 1. Moreover, rationality implies that there should not be (time) serial correlation in the disturbances for all i and all $|t-s|>k$, where k is the number of overlapping forecast periods. However, assuming that all forecasters are surprised by the same aggregate shocks to the economy, disturbances are correlated across units within each period.

More precisely, the following assumptions have been made:

$$E(u_{it}^2) = \sigma_i^2 \qquad \text{for all } t=1,\dots,T \ ; \ i=1,\dots,N \tag{4}$$

$$E(u_{it}u_{jt}) = \rho\sigma_i\sigma_j \qquad \text{for all } t \text{ and } i \neq j. \tag{5}$$

$$E(u_{it}u_{is}) = \begin{cases} 0 & \text{for all } i \text{ and } |t-s|>k \\ \rho_{-s,i}\ \sigma_i^2 & \text{for all } i \text{ and } |t-s|\leq k \end{cases} \tag{6}$$

$$E(u_{it}u_{js}) = \begin{cases} 0 & \text{for all } i,j,\ i\neq j, \text{ and } |t-s|>k \\ \rho_{-s}\sigma_i\sigma_j & \text{for all } i,j,\ i\neq j, \text{ and } |t-s|\leq k \end{cases} \tag{7}$$

This specification allows for heteroscedasticity of the disturbances across units, for non-zero contemporaneous correlation between the disturbances in different units, and for lagged correlation within and between disturbances for overlapping forecast horizons. The common correlation coefficient ρ reflects the assumption of an aggregate shock to the economy. The resulting (TNxTN) variance/covariance matrix for the disturbances terms, here for k=1, looks as follows:

$$\Omega = \begin{bmatrix} \Gamma & \Phi & 0 & & \cdots & & 0 \\ \Phi & \Gamma & \Phi & 0 & & & \\ 0 & \Phi & \Gamma & \Phi & 0 & & \\ \vdots & & & \ddots & & \Phi & 0 \\ & & & & \Phi & \Gamma & \Phi \\ 0 & & & & 0 & \Phi & \Gamma \end{bmatrix} \tag{8}$$

where:

$$\Gamma_{(N\times N)} = \begin{bmatrix} \sigma_1 & & 0 \\ & \ddots & \\ 0 & & \sigma_N \end{bmatrix} \begin{bmatrix} 1 & & \rho \\ & \ddots & \\ \rho & & 1 \end{bmatrix} \begin{bmatrix} \sigma_1 & & 0 \\ & \ddots & \\ 0 & & \sigma_N \end{bmatrix}$$

and:

$$\Phi_{(N\times N)} = \begin{bmatrix} \sigma_1 & & 0 \\ & \ddots & \\ 0 & & \sigma_N \end{bmatrix} \begin{bmatrix} \rho_{-s,1} & & \rho_{-s} \\ & \ddots & \\ \rho_{-s} & & \rho_{-s,N} \end{bmatrix} \begin{bmatrix} \sigma_1 & & 0 \\ & \ddots & \\ 0 & & \sigma_N \end{bmatrix}$$

In a first step, individual OLS regressions were run for all i to obtain individual residual series e_i. These series were used to estimate the elements of Γ and Φ and thus to obtain an estimate of Ω. The estimators for σ_i, ρ and ρ_{-s} are:

$$\hat{\sigma}_i = \sqrt{\frac{e_i'e_i}{T-2}} \quad ,$$

$$\hat{\rho} = \frac{\sum_{i\neq j} corr_{ij} * (N_{ij}-1)}{\sum_{i\neq j} (N_{ij}-1)} \quad ,$$

and:

$$\hat{\rho}_{-s} = \frac{\sum_{i \neq j} \text{corr}_{-s,ij} * (N_{-s,ij} - 1)}{\sum_{i \neq j} (N_{-s,ij} - 1)}$$

where N_{ij} is the number of observations with non-missing forecasts for both participants i and j and (-s) indicates a lag. In a second step, the stacked regression (3) was run with the consistent estimate of the variance/covariance matrix:

$$\text{cov}_{\hat{b}} = (X'X)^{-1}X'\hat{\Omega}\, X\, (X'X)^{-1}$$

This is a formulation analogous to the White heteroscedasticity consistent variance/covariance estimates with OLS.[4] The results of a first round of regressions are summarized in Table 2a. Unbiasedness was rejected in all six regressions, even in the third-month-forecast of the current quarter. As an additional step, different specifications of the variance/covariance matrix Ω were tried to see whether the results are sensitive to such changes. Table 2b reports the various t-statistics that resulted from different variance/covariance estimates. As can been seen, the t-statistics (i.e., the standard error estimates which are not

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[4] The computationally most burdensome task was to deal with missing observations. Most software would just cancel all periods containing missing obersations. However, with stacked data, the dimension of the individual blocks had to be maintained. For the stacked OLS regression, consequently zeros were added in both matrix **X** and vector **Y** whenever one observation was missing which is equivalent to cancelling the observation because one adds zero to the explained sum of squares. Care must be taken, however, to correct for the true number of observations whenever necessary. For the estimation of the elements of Omega, only periods were considered where residuals for both of any two individual regressions had been obtained. All routines were written in the matrix-language package of SAS.

reported since the OLS coefficient estimates are the same) remain virtually stable over different specifications of Ω.

A possible caveat remains that neither interest rate series nor the individual forecast series seem to be stationary (see figures 1 and 3). This casts some doubt on the test for unbiasedness. However, the series are too short for meaningful analysis of their time series properties individually and in relation to each other. This is a drawback of the data which was also chosen to exploit the cross-section dimension. In the remainder of this paper, efficiency tests have therefore been chosen that make sure that regressands and regressors are stationary series under the null hypothesis of Rational Expectations.

4. Testing for Idiosyncracies

A second consequence of the Rational Expectations Hypothesis implies the efficient use of readily available information. Such information should not explain forecast errors, otherwise it could have been used to improve the forecast. In this section, a first run of regressions is presented that tests for the presence of idiosyncratic errors. In these tests the dependent variable, i.e. the idiosyncratic forecast error, is stationary under the null hypothesis. The only explanatory variable for the time being is a constant -- stationary as well. Since we test for idiosyncracies, the data was not pooled. Instead, all 23 series of idiosyncratic forecasts errors were regressed seperately on a constant. For the current-quarter idiosyncratic forecast errors, simple OLS regressions were run:

$$(err_t^{i,t}-err_t^{ave,t}) = \gamma^i + u_t^i \tag{9}$$

where the left-hand side is the individual forecast error minus the average forecast error in period t made in the current period t, γ^i is a constant, and u_t^i are n.i.i.d. disturbances with mean zero and variance σ_u^2. For the one-quarter-ahead idiosyncratic forecasts errors, the standard errors of the OLS regressions have been corrected allowing for a first-order moving-average process in the error term.

$$\begin{aligned} (err_t^{i,t-1} - err_t^{ave,t-1}) &= \delta^i + v_t^i \\ v_t^i &= \varepsilon_t^i - \zeta^i \varepsilon_{t-1}^i \end{aligned} \tag{10}$$

where ε_t^i is n.i.i.d. with mean zero and variance $\sigma_{\varepsilon,i}^2$ and ζ^i are the individual parameters of the MA(1)-process. The consistent variance/covariance estimate is:

$$cov_{\hat{\gamma}^i} = (X_i'X_i)^{-1} X_i' \hat{\Psi}^i X_i (X_i'X_i)^{-1}$$

where:

$$\hat{\Psi}_i = \begin{bmatrix} \hat{\sigma}_i^2 & \hat{\zeta}_i \hat{\sigma}_i^2 & 0 & \dots & 0 \\ \hat{\zeta}_i \hat{\sigma}_i^2 & \hat{\sigma}_i^2 & \hat{\zeta}_i \hat{\sigma}_i^2 & & \\ 0 & \hat{\zeta}_i \hat{\sigma}_i^2 & \ddots & & \\ \vdots & & & & \hat{\zeta}_i \hat{\sigma}_i^2 \\ 0 & & & \hat{\zeta}_i \hat{\sigma}_i^2 & \hat{\sigma}_i^2 \end{bmatrix}$$

The results of these 138 (23x6) individual regressions are summarized in tables 3a-f. How does one evaluate the estimation of so many different regressions ? One conservative way of maintaining a constant overall significance level for the null hypothesis of all intercept terms equal to zero is to use the Bonferroni t-statistics which does not use the α-point of the t-distribution but the (α/r)-point where r is the number of individual tests.

Applying the Bonferroni criterion to all 138 (23x6) regressions, keeping an α=0.05-overall significance level, the null hypothesis of no idiosyncratic forecast errors for the entrie set of regressions is rejected. There are two t-statistics higher than their individual critical value, 4.322 for 19 degrees of freedom (participant L) and 4.278 for 20 degrees of freedom (participant U). The critical values come from the tables published by Bailey [1977].

The critical Bonferroni t-statistic, keeping a constant α=0.05-overall significance level for each participant, there are six regressions per individual, would be for the average number of degrees of freedom approximately 2.984 (the 0.05/6-point of the t-distribution). With this criterion, the null of no idiosyncratic errors is rejected for nine out of the 23 survey participants. Note that in most regression series constants with different signs result individually significantly different from zero. Participants in this survey systematically make idiosyncratic errors in either direction away from the mean forecast.

5. Testing for Efficiency

The implication of the Rational Expectation Hypothesis that available information should not be able to statistically explain the forecast error -- otherwise it could have been used -- can be extended to a variety of explanatory variables. This has been done in the present section.

The regression analysis summarized in the following tables has been guided by two ideas. The first is to see whether survey forecasts exploit efficiently the information that is contained in the past information about the predicted variable. The second is to see whether the sample forecasters use economic theory and relationships with other variables when predicting interest rates. All regression are pooled, with estimated standard errors corrected for correlation among forecasters. The covariance matrix for the White-like-consistent standard errors has been obtained from first-step individual regressions.

The first group of efficiency tests seeked to establish whether forecast participants should have moved towards the past average forecast published each month alongside the individual forecasts. Table 4a summarizes the results of pooled regressions of the individual forecast errors on the difference between the past average minus the individual forecast. Under the null hypothesis of Rational Exectations, the regression coefficient of this term should be zero. As can be seen in table 4a, the forecast errors are explained to a large extent by the failure to exploit the information content in the past mean forecast which has implicitly pooled individual information about the variable at hand. The corresponding regression coefficients are highly significant with t-statistics varying from 4.3 to 20.5. To make sure that these results are not due to lacking knowledge of the past average, similar regressions have been repeated for the difference between the lagged past average forecast and the individual prediction, as is summarized in table 4b. The coefficient estimates are a little lower but still significant in this case.

The second efficiency test seeked to establish whether the forecasted change is explained by the past changes in the predicted variable. These regressions are summarized in table 5. The survey participants clearly use past quarterly changes for prediction purposes, that is, they extrapolate. All estimated regression coefficients are statistically significant, the explanatory power of past quarterly changes for the forecasted quarterly change, as measured by the R^2-statistics, ranges from 0.17 to 0.42. Similar regressions were repeated using the forecasted change in a given month and the previous monthly change of the discount rate on new 91-day T-Bills. Tables 6a-c show the results of three such regressions which produced one significant and two non-significant coefficient estimates.

One of the reasons why expectations are not rational might be the fact that different economic agents use different theories when formulating their forecasts. This idea has been exploited in the efficiency tests summarized in table 7 which regressed the forecast error on the past quarter's spread between the six-month and the three-month Treasury Bill. The coefficient estimates are positive, but not significant. Statistically significant positive regression coefficients would mean that the under-prediction of the interest rate increases with the spread, i.e., forecasters would not use the term structure of the interests rate.

Table 8 summarizes the results of regressions that seeked to establish whether forecasters used the Fisher hypothesis that the expected real interest rate is constant and that expected nominal interst rate and expected inflation rates move together. As dependent variable the idiosyncratic interest rate forecast was regressed on the idiosyncratic price forecast for the same target period. Again, the regression coefficients were not significantly different from zero, i.e., there is no statistically significant, subjective Fisher effect.

6. Revision vs. Precision

The use of survey data for testing the Rational Expectations Hypothesis has been generally questioned on the grounds that forecasters might not act upon their public announcement in the market place, or, that their public forecast might be the solution to a more intricate private optimization problem. This section addresses this possibility. Salmon/Waldmann (1991) proposed a principal-agent game between financial consultants and consultees that features an underlying private optimization problem. Their model implies that errors in the publicly announced forecasts occur systematically and that these errors can be predicted by changes from past public forecasts for the same target period. The argument would be that the change does not fully reflect the true revision because fincancial consultants are relunctant to admit they were wrong with earlier predictions.

The hypothesis can be tested by regressing forecast errors on changes in past forecasts for the same target quarter. This is a special case of efficiency test as discussed in section 2, providing a rationale for a non-zero coefficient for a variable in the information set known when the forecast was made. It implies an intercept term of zero and a positive regression coefficient on the past changes in the following regression:

$$(X_{t,m} - X^{e}_{t,m}) = \lambda_0 + \lambda_1 (X^{e}_{t,m} - X^{e}_{t,m-i}) + u_t \qquad (11)$$

where e-superscript, t-superscript now denote public annoucements for period t; t-subscript is the target quarter and (m-i) indicates the month in which the forecasts was made with m>i>0 and m=2,3 and i=1,2; and u_t is a n.i.i.d error term with zero mean and variance σ^2_u. The positive regression coefficient means that the forecast could have been improved by adding a (possibly small) constant multiplied by the change in the public announcements to adjust for the forecasters' relunctance to revise their earlier forecasts.

Note, that under the Rational Expectations Hypothesis the expected value of the coefficient λ_1 would be zero. Rational Expectations imply that changes in expectations follow a random walk. For $X^{e,t-1}_t = E[X|I_{t-1}]$:

$$E[X^{e,t+1}_{t+1}|I_t] = E[\,E(X|I_t,\omega_{t+1})\mid I_t\,] = E[X|I_t] \qquad (12)$$

$$\Rightarrow \quad X^{e,t+1}_{t+1} = X^{e,t}_{t+1} + \varepsilon_{t+1} \qquad (13)$$

When pooling the data for regression (11), forecast errors are again likely to be correlated across agents. Therefore, the same two-step procedure as in section 3 needs to be applied. Individual regressions yield individual residual series which, in turn, can be used to estimate the error term variance/covariance matrix Ω for the consistent variance/covariance estimates of $\hat{\lambda}$. The tests were run for current quarter forecast errors regressed on the change in the third month forecast from the second month forecast, the change of the third from the first month forecast, and the change of the second from the first month forecast resp. The results are summarized in table 8.

In all three regressions, the coefficients have the wrong sign, and significantly so. It does not seem that publicy-announced forecasts were meant to mask the unwillingness of forecasters to revise past announcements for the same target period. To the contrary, it seems that the survey participants over-react in their changes. Subtracting a (possibly) small constant multiplied by their change in announcement would improve their forecast, not adding as had been hypothesized.

7. Summary

This paper presents some evidence rejecting the conventional Rational Expectation Hypothesis. Tests with pooled data of interest rate forecasts from a commercial newsletter rejected the implication of unbiased forecasts. Tests with the individual data rejected the null hypothesis of no systematic idiosyncratic components in forecast errors.

A number of efficiency tests with the pooled data rejected the implication of Rational Expectations that available information be incorporated in predictions. Survey participants ignored, for example, the information contained in the past average forecast and seemed to over-extrapolate past trends in interest rates. However, regressions with right-hand side variables as suggested by the different use of economic theory when predicting interest rates did not produce statistically significant coefficient estimates. Lastly, an alternative behavioral model explaining forecasts errors with the forecasters' unwilligness to revise previous predictions for the same target period too much was rejected.

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APPENDIX 1

This appendix compares the OLS estimators in tests of unbiasedness as used in section (3) for a survey mean forecast and for pooled survey data. It is shown that the estimate for the coefficient on the mean forecast is upward biased as long as there is the cross-sectional variation in the individual forecast.[5]

The OLS estimator for the survey mean is:

$$\hat{\beta}_m = \frac{\sum_{t=1}^{T} (Y_t - \bar{Y})(X_t - \bar{X})}{\sum_{t=1}^{T} (X_t - \bar{X})^2} \tag{A.1}$$

The OLS estimator for the pooled data is:

$$\hat{\beta}_p = \frac{\sum_{t=1}^{T} \sum_{i=1}^{N} (Y_{it} - \bar{Y})(X_{it} - \bar{X})}{\sum_{t=1}^{T} \sum_{i=1}^{N} (X_{it} - \bar{X})^2} \tag{A.2}$$

where:

$$X_t = \frac{1}{N} \sum_{i=1}^{I} X_{it} \quad , \quad \bar{X} = \frac{1}{T} \sum_{t=1}^{T} X_t = \frac{1}{N} \frac{1}{T} \sum_{t=1}^{T} \sum_{i=1}^{N} X_{it}$$

and:

[5]This has been noticed first by Dietrich/Joines [1983], and then by Urich/Wachtel [1984] and Keane/Runkle [1990].

$$\bar{Y} = \frac{1}{T}\sum_{t=1}^{T} Y_t$$ note that by definition $Y_{1t} \equiv Y_t$.

Expanding the numerator of (A.1), using the definitions of the averages above, gives:

$$\sum_{t=1}^{T} (Y_t-\bar{Y})(X_t-\bar{X}) = \sum_{t=1}^{T} (Y_tX_t - \bar{X}\,Y_t - \bar{Y}\,X_t + \bar{X}\,\bar{Y}\,)$$

$$= \sum_{t=1}^{T} Y_tX_t - \frac{1}{T}\sum_{t=1}^{T}\sum_{t=1}^{T} Y_tX_t - \frac{1}{T}\sum_{t=1}^{T}\sum_{t=1}^{T} Y_tX_t + \sum_{t=1}^{T}\frac{1}{T}\sum_{t=1}^{T} Y_t \frac{1}{T}\sum_{t=1}^{T} X_t$$

$$= \sum_{t=1}^{T} Y_tX_t - \frac{1}{T}\sum_{t=1}^{T}\sum_{t=1}^{T} Y_tX_t - \frac{1}{T}\sum_{t=1}^{T}\sum_{t=1}^{T} Y_tX_t + \frac{1}{T}\sum_{t=1}^{T}\sum_{t=1}^{T} Y_tX_t$$

$$= \sum_{t=1}^{T} Y_tX_t - \frac{1}{T}\sum_{t=1}^{T} Y_t \sum_{t=1}^{T} X_t = \sum_{t=1}^{T} Y_tX_t - T\frac{1}{T}\sum_{t=1}^{T} Y_t \frac{1}{T}\sum_{t=1}^{T} X_t$$

$$= \sum_{t=1}^{T} Y_tX_t - T\,\bar{Y}\,\bar{X} \qquad \text{(A.3)}$$

Similarly, expanding the denominator of (A.1), gives:

$$\sum_{t=1}^{T} (X_t-\bar{X})^2 = \sum_{t=1}^{T} (X_t^2 + \bar{X}^2 - 2\,X_t\bar{X})$$

$$= \sum_{t=1}^{T} X_t^2 + T\,\bar{X}^2 - 2\,\bar{X}\sum_{t=1}^{T} X_t$$

$$= \sum_{t=1}^{T} X_t^2 + T\,\bar{X}^2 - 2\,T\frac{1}{T}\sum_{t=1}^{T} X_t \frac{1}{T}\sum_{t=1}^{T} X_t = \sum_{t=1}^{T} X_t^2 + T\,\bar{X}^2 - 2\;T\,\bar{X}^2$$

$$= \sum_{t=1}^{T} X_t^2 - T\,\bar{X}^2 \tag{A.4}$$

Expanding the numerator in (A.2), gives:

$$\sum_{t=1}^{T} \sum_{i=1}^{N} (Y_{it}-\bar{Y})(X_{it}-\bar{X}) = \sum_{t=1}^{T} \sum_{i=1}^{N} (Y_{it}X_{it} - \bar{Y}X_{it} - \bar{X}Y_{it} + \bar{Y}\bar{X})$$

$$= N \sum_{t=1}^{T} Y_t \frac{1}{N} \sum_{i=1}^{N} X_{it} - N\,\bar{Y} \sum_{t=1}^{T} \frac{1}{N} \sum_{i=1}^{N} X_{it} - \bar{X} \sum_{i=1}^{N}\sum_{t=1}^{T} Y_t + TN\,\bar{Y}\,\bar{X}$$

$$= N \sum_{t=1}^{T} Y_t X_t - N\,T\,\bar{Y}\,\frac{1}{T}\sum_{t=1}^{T} X_t - N\,T\,\bar{X}\,\frac{1}{T}\sum_{t=1}^{T} Y_t + TN\,\bar{Y}\,\bar{X}$$

$$= N \sum_{t=1}^{T} Y_t X_t - N\,T\,\bar{Y}\,\bar{X} = N\left(\sum_{t=1}^{T} Y_t X_t - T\,\bar{Y}\,\bar{X}\right) \tag{A.5}$$

Note, that the nominator of $\hat{\beta}_p$ is equal to nominator of $\hat{\beta}_m$ multiplied by N. Hence, $\hat{\beta}_p$ will only equal $\hat{\beta}_m$ if there is an equal relationship between the denominators. Expanding the denominator of (A.2) using the same trick as before for the denominator of (A.1) gives:

$$\sum_{t=1}^{T} \sum_{i=1}^{N} (X_{it}-\bar{X})^2 = \sum_{t=1}^{T} \sum_{i=1}^{N} X_{it}^2 - T\,N\,\bar{X}^2$$

$$= \sum_{t=1}^{T} \sum_{i=1}^{N} X_{it}^2 - N \sum_{t=1}^{T} X_t^2 + N \sum_{t=1}^{T} X_t^2 - T\,N\,\bar{X}^2$$

$$= N\left[\sum_{t=1}^{T} X_t^2 - T\,\bar{X}^2\right] + \sum_{t=1}^{T}\left[\sum_{i=1}^{N} X_{it}^2 - N\,X_t^2\right]$$

$$= N\left[\sum_{t=1}^{T} X_t^2 - T\,\bar{X}^2\right] + \sum_{t=1}^{T}\sum_{i=1}^{N} X_{it}^2 - N \sum_{t=1}^{T} X_t^2$$

$$= N\left[\sum_{t=1}^{T} X_t^2 - T\,\overline{X}^2\right] + \sum_{t=1}^{T}\sum_{i=1}^{N} X_{it}^{\,2} + N\sum_{t=1}^{T} X_t^2 - 2N\sum_{t=1}^{T} X_t^2$$

$$= N\left[\sum_{t=1}^{T} X_t^2 - T\,\overline{X}^2\right] + \sum_{t=1}^{T}\sum_{i=1}^{N} X_{it}^{\,2} + \sum_{i=1}^{N}\sum_{t=1}^{T} X_t^2 - 2N\sum_{t=1}^{T} X_t \frac{1}{N}\sum_{i=1}^{N} X_{it}$$

$$= N\left[\sum_{t=1}^{T} X_t^2 - T\,\overline{X}^2\right] + \sum_{t=1}^{T}\sum_{i=1}^{N} X_{it}^{\,2} + \sum_{i=1}^{N}\sum_{t=1}^{T} X_t^2 - 2\sum_{t=1}^{T}\sum_{i=1}^{N} X_t X_{it}$$

$$= N\left[\sum_{t=1}^{T} X_t^2 - T\,\overline{X}^2\right] + \sum_{t=1}^{T}\sum_{i=1}^{N}\left[X_{it} - X_t\right]^2 \qquad \text{(A.6)}$$

Note that the first term in the denominator of $\hat{\beta}_p$ is equal to the denominator of $\hat{\beta}_m$ multiplied by N. This means, the two estimators are only identical if the second term in (A.6) vanishes which is only the case if there is no cross-sectional variation in the forecasts X_{it} of the event Y.

Urich/Wachtel [1984] report the regressions results for the mean of all individual equation-(3)-type regressions, the result of the pooled regression, and the result of the realization on the survey mean forecast.

Estimates	$\hat{\beta}_0$	$\hat{\beta}_1$
Realization on Forecasts		
Mean of Individual Forecasts	-0.13	0.78
Pooled Data	-0.12	0.77
Sample Means	-0.29	1.06

This shows how important the upward aggregation bias in regressions using the sample mean as opposed to pooled data can be.

APPENDIX 2

This appendix demonstrates that the conditional expectation is the optimal prediction of a variable if agents have a quadratic loss function. Let J be the loss function:

$$J = \int_{-\infty}^{\infty} a \left[x - f \right]^2 \; h_c(x)\, dx \tag{A.7}$$

where a is a constant, x the variable predicted, f the prediction made in period t-1, h_c the conditional probability density function of X_t given the information set I_{t-1}. Let additionally be M_c the conditional of X_t given
I_{t-1}:

$$M_c = \int_{-\infty}^{\infty} x\, h_c(x)\, dx$$

Then, expanding the loss function gives:

$$J = \int_{-\infty}^{\infty} a \left[x^2 + (f)^2 - 2\, x\, f \right] h_c(x)\, dx$$

$$= \int_{-\infty}^{\infty} a\, x^2\, h_c(x)dx + af^2 \int_{-\infty}^{\infty} h_c(x)dx - 2af \int_{-\infty}^{\infty} x\, h_c(x)\, dx$$

$$= \int_{-\infty}^{\infty} ax^2\, h_c(x)dx + af^2 - 2af\, M_c$$

$$= \int_{-\infty}^{\infty} ax^2 \ h_c(x)dx + af^2 - 2af\ M_c + a\ M_c^2 - a\ M_c^2$$

$$= a\left(M_c - f\right)^2 + \int_{-\infty}^{\infty} ax^2\ h_c(x)dx - a\ M_c^2$$

$$= a\left(M_c - f\right)^2 + \int_{-\infty}^{\infty} ax^2\ h_c(x)dx + a\left(M_c^2 - 2\ M_c^2\right)$$

$$= a\left(M_c - f\right)^2 + \int_{-\infty}^{\infty} ax^2\ h_c(x)dx + a\left(M_c^2 \int_{-\infty}^{\infty} h_c(x)dx - 2M_c \int_{-\infty}^{\infty} x\ h_c(x)dx\right)$$

$$= a\left(M_c - f\right)^2 + \int_{-\infty}^{\infty} ax^2\ h_c(x)dx + \int_{-\infty}^{\infty} a\ (M_c^2 - 2M_c x)\ h_c(x)dx$$

$$= a\left(M_c - f\right)^2 + \int_{-\infty}^{\infty} a\ (x - M_c)^2\ h_c(x)dx \qquad (A.8)$$

The forecast f only appears in the first term of expression (A.8) so the loss function J is minimized by taking

$$f = M_c = E_c\ [X_t \mid I_{t-1}]$$

TABLE 1

Results from the U.S. T-Bill Auction in the first week of June 1991

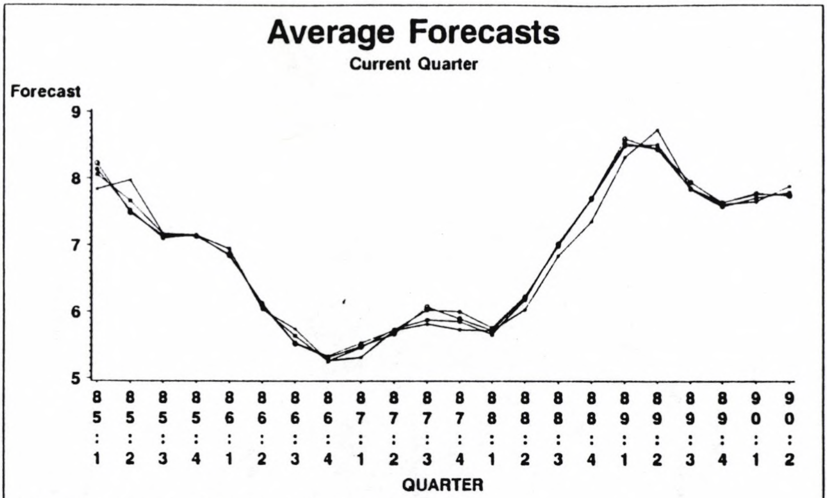
"RATES ARE DETERMINED BY THE DIFFERENCE BETWEEN THE PURCHASED PRICE AND FACE VALUE. THUS, HIGHER BIDDING NARROWS THE INVESTOR'S RETURN WHILE LOWER BIDDING WIDENS IT. THE PERCENTAGE RATES ARE CALCULATED ON A 360-DAY YEAR, WHILE THE COUPON EQUIVALENT YIELD IS BASED ON A 366-DAY YEAR.

	13-WEEK	26-WEEK
APPLCIATIONS	$ 31,146,835,000	$ 27,966,945,000
ACCEPTED BIDS	$ 10,024,925,000	$ 10,000,975,000
ACCEPTED AT LOW PRICE	10 %	28 %
ACCEPTED NONCOMPET'TLY	$ 1,567,110,000	$ 1,143,980,000
AVERAGE PRICE (RATE)	98.587 (5.59%)	97.113 (5.71%)
HIGH PRICE (RATE)	98.592 (5.57%)	97.128 (5.68%)
LOW PRICE (RATE)	98.584 (5.60%)	97.108 (5.72%)
COUPON EQUIVALENT	5.76 %	5.98 %
CUSIP NUMBER	912794XE9	912794XQ2

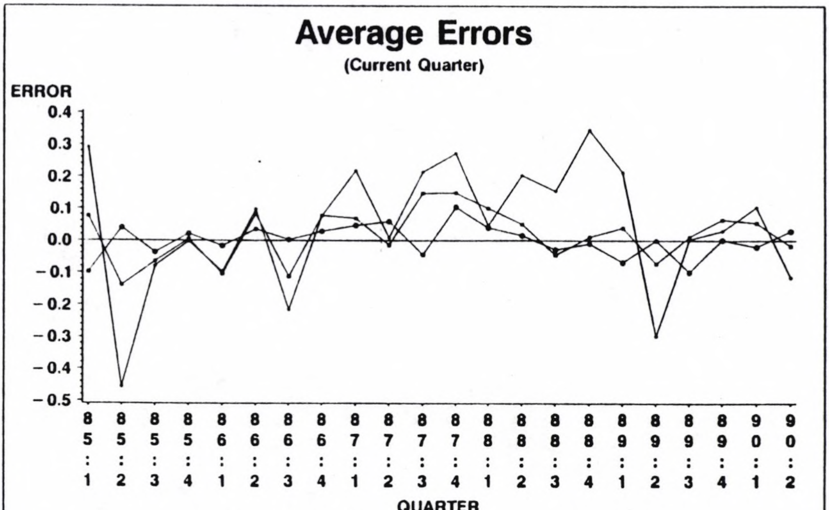
BOTH ISSUES ARE DATED JUNE 6, 1991. THE 13-WEEK BILLS MATURE SEPTEMBER 5, 1991, AND THE 26-WEEK BILLS MATURE DECEMBER 5, 1991."

(Source: Wall Street Journal, June 4, 1991)

FIGURE 1 - 2

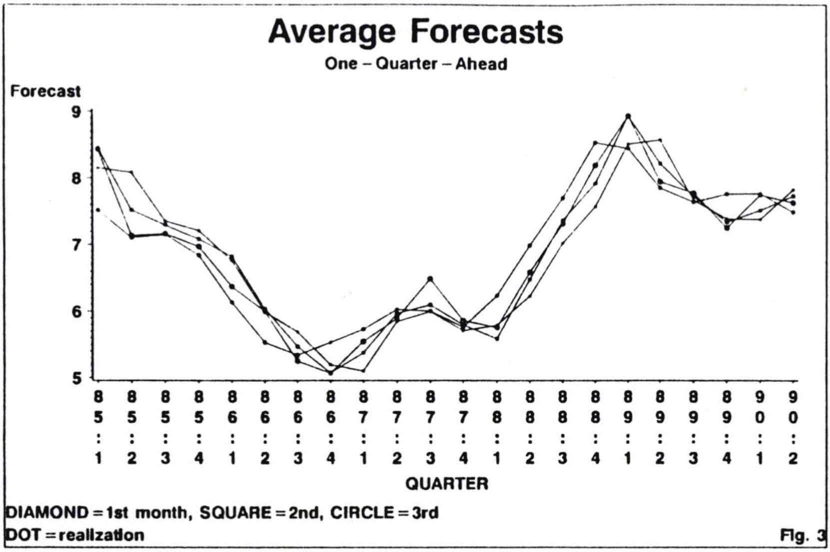


DIAMOND = 1st month, SQUARE = 2nd, CIRCLE = 3rd
DOT = realization
Fig. 1



DIAMOND = 1st month, SQUARE = 2nd, CIRCLE = 3rd
Fig. 2

FIGURE 3 - 4


Average Forecasts
One – Quarter – Ahead
Forecast
9
8
7
6
5
85:1 85:2 85:3 85:4 86:1 86:2 86:3 86:4 87:1 87:2 87:3 87:4 88:1 88:2 88:3 88:4 89:1 89:2 89:3 89:4 90:1 90:2
QUARTER
DIAMOND = 1st month, SQUARE = 2nd, CIRCLE = 3rd
DOT = realization
Fig. 3

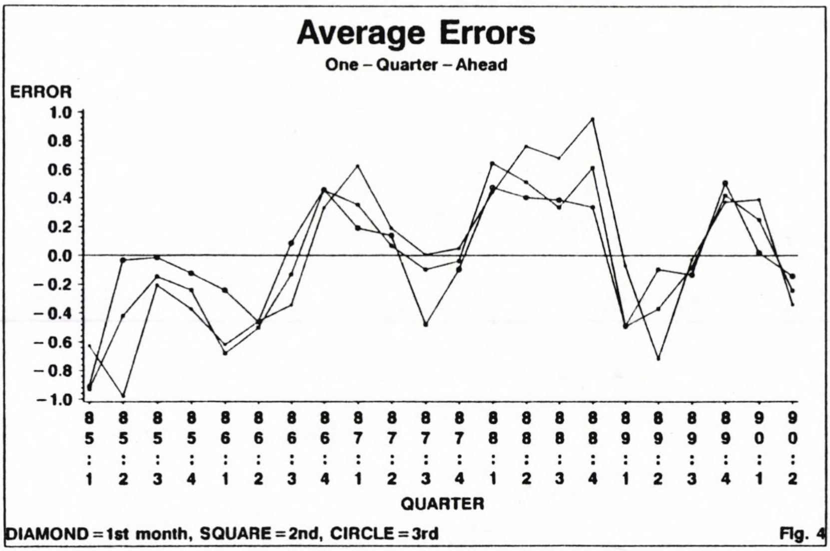

Average Errors
One – Quarter – Ahead
ERROR
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6
−0.8
−1.0
85:1 85:2 85:3 85:4 86:1 86:2 86:3 86:4 87:1 87:2 87:3 87:4 88:1 88:2 88:3 88:4 89:1 89:2 89:3 89:4 90:1 90:2
QUARTER
DIAMOND = 1st month, SQUARE = 2nd, CIRCLE = 3rd
Fig. 4

TABLE 2A

Tests for Unbiasedness of Forecasts*

Dependent Variable: Outcome

	Regression	Constant	Forecast	ρ	ρlag
1.	Current Quarter First Month	0.80 (2.91)	0.89 (2.80)	0.47	
	R^2=0.91, N = 433				
2.	Current Quarter Second Month	0.49 (3.57)	0.93 (3.52)	0.18	
	R^2=0.95, N = 435				
3.	Current Quarter Third Month	0.23 (3.05)	0.97 (3.02)	0.11	
	R^2=0.98, N = 440				
4.	One-Q-Ahead First Month	2.26 (2.66)	0.67 (2.76)	0.78	0.49
	R^2=0.63, N = 433				
5.	One-Q-Ahead Second Month	1.85 (2.51)	0.72 (2.64)	0.79	0.47
	R^2=0.73, N = 435				
6.	One-Q-Ahead Third Month	1.34 (2.52)	0.80 (2.60)	0.65	0.19
	R^2=0.81, N = 430				

*OLS-estimates with corrected standard errors. In parentheses t-statistics for the hypothesis of zero coefficient for the constant term and unitary coefficient for the forecast term. Data as described in section 2.

TABLE 2B

Tests for Unbiasedness

Alternative Specifications for the covariance estimation

1.	Current Quarter First Month	t for Constant	t for Forecast	$\hat{Var}$	$\hat{Covar}$
a.	Single Var, Single Covar	2.93	2.80	0.088	0.039
b.	Var Free, Single Covar	2.93	2.81		
c.	Var Free, Covar Free	2.94	2.82		

2.	Current Quarter Second Month	t for Constant	t for Forecast	$\hat{Var}$	$\hat{Covar}$
a.	Single Var, Single Covar	4.01	3.93	0.053	0.0054
b.	Var Free, Single Covar	3.96	3.89		
c.	Var Free, Covar Free	3.93	3.87		

3.	Current Quarter Third Month	t for Constant	t for Forecast	$\hat{Var}$	$\hat{Covar}$
a.	Single Var, Single Covar	2.86	2.82	0.024	0.0026
b.	Var Free, Single Covar	2.85	2.81		
c.	Var Free, Covar Free	2.81	2.79		

TABLE 2B (CONTINUED)

4.	One-Q-Ahead First Month	t for Constant	t for Forecast	Var Vlag	Covar Colag
a.	Single Var, Single Covar	2.60	2.70	0.341 0.158	0.241 0.176
b.	Var Free, Single Covar	2.60	2.70		
c.	Var Free, Covar Free	2.59	2.68		

5.	One-Q-Ahead Second Month	t for Constant	t for Forecast	Var Vlag	Covar Colag
a.	Single Var, Single Covar	2.51	2.63	0.249 0.111	0.174 0.113
b.	Var Free, Single Covar	2.50	2.63		
c.	Var Free, Covar Free	2.49	2.68		

6.	One-Q-Ahead Third Month	t for Constant	t for Forecast	Var Vlag	Covar Colag
a.	Single Var, Single Covar	2.48	2.56	0.181 0.052	0.115 0.037
b.	Var Free, Single Covar	2.47	2.56		
c.	Var Free, Covar Free	2.47	2.55		

TABLE 3A

Tests for Idiosyncratic Bias*

Dependent Variable: Idiosyncratic Error ($err_i - err_{ave}$)

	Regression	Constant	t for H_0: γ =0
	Current Quarter First Month		
1.	Participant A	-0.158	-3.447‡
2.	Participant B	0.078	2.824
3.	Participant C	-0.107	-1.730
4.	Participant D	-0.013	-0.291
5.	Participant E	-0.068	-0.994
6.	Participant F	-0.010	-0.322
7.	Participant G	-0.154	-1.891
8.	Participant H	0.024	0.546
9.	Participant I	-0.015	-0.143
10.	Participant J	0.055	0.782
11.	Participant K	-0.062	-1.355
12.	Participant L	0.172	3.233‡
13.	Participant M	0.015	0.251
14.	Participant N	0.068	2.459
15.	Participant O	-0.036	-0.646
16.	Participant P	0.122	3.087‡
17.	Participant Q	0.060	1.266
18.	Participant R	-0.014	-0.187
19.	Participant S	-0.009	-0.342
20.	Participant T	0.163	2.306
21.	Participant U	-0.027	-0.593
22.	Participant V	0.017	0.355
23.	Participant X	-0.066	-1.133

*OLS regressions. Data as described in section 2. ‡Rejects for the individual at the α=0.05-overall significance level for six regressions.

Table 3B

Tests for Idiosyncratic Bias*

Dependent Variable: Idiosyncratic Error ($err_i - err_{ave}$)

	Regression	Constant	t for H_0: γ =0
	Current Quarter Second Month		
1.	Participant A	-0.146	-3.290‡
2.	Participant B	-0.023	-0.692
3.	Participant C	-0.053	-0.929
4.	Participant D	-0.018	-1.098
5.	Participant E	0.005	0.162
6.	Participant F	-0.032	-1.779
7.	Participant G	-0.061	-1.850
8.	Participant H	-0.045	-0.990
9.	Participant I	0.154	1.199
10.	Participant J	-0.099	-1.861
11.	Participant K	-0.033	-1.122
12.	Participant L	0.057	1.295
13.	Participant M	0.066	1.413
14.	Participant N	-0.001	-0.027
15.	Participant O	-0.022	-0.875
16.	Participant P	0.096	2.401
17.	Participant Q	-0.016	-0.646
18.	Participant R	0.044	1.243
19.	Participant S	-0.024	-1.601
20.	Participant T	0.207	2.328
21.	Participant U	0.029	0.895
22.	Participant V	-0.018	-0.354
23.	Participant X	-0.070	-2.388

*OLS regressions. Data as described in section 2. ‡Rejects for the individual at the α=0.05-overall significance level for six regressions.

TABLE 3C

Tests for Idiosyncratic Bias*

Dependent Variable: Idiosyncratic Error $(err_i - err_{ave})$

	Regression	Constant	t for H_0: $\gamma = 0$
	Current Quarter Third Month		
1.	Participant A	-0.044	-1.459
2.	Participant B	0.018	1.639
3.	Participant C	-0.016	-0.515
4.	Participant D	-0.026	-0.638
5.	Participant E	0.018	0.821
6.	Participant F	0.034	1.404
7.	Participant G	-0.065	-2.509
8.	Participant H	-0.103	-2.089
9.	Participant I	0.027	0.468
10.	Participant J	0.103	1.631
11.	Participant K	-0.044	-2.076
12.	Participant L	0.029	1.272
13.	Participant M	0.128	3.216‡
14.	Participant N	-0.004	-0.169
15.	Participant O	-0.007	-0.381
16.	Participant P	0.078	2.026
17.	Participant Q	-0.011	-0.478
18.	Participant R	-0.022	-0.844
19.	Participant S	0.005	0.594
20.	Participant T	0.022	0.388
21.	Participant U	-0.021	-0.910
22.	Participant V	-0.022	-0.736
23.	Participant X	-0.021	-0.998

*OLS regressions. Data as described in section 2. ‡Rejects for the individual at the α=0.05-overall significance level for six regressions.

Table 3D

Tests for Idiosyncratic Bias*

Dependent Variable: Idiosyncratic Error $(err_i - err_{ave})$

	Regression	Constant	t for H_0: δ=0	MA(1)
	One-Q-Ahead First Month			
1.	Participant A	-0.325	-2.277	0.485
2.	Participant B	0.176	3.251‡	-0.064
3.	Participant C	-0.255	-0.759	0.459
4.	Participant D	-0.071	-0.724	0.274
5.	Participant E	-0.050	-0.291	0.509
6.	Participant F	0.101	1.430	0.151
7.	Participant G	-0.487	-2.337	0.477
8.	Participant H	0.114	1.302	0.143
9.	Participant I	0.191	0.932	0.189
10.	Participant J	-0.121	-0.625	0.799
11.	Participant K	-0.015	-0.105	0.571
12.	Participant L	0.372	5.531‡‡	-0.024
13.	Participant M	-0.106	-0.592	0.248
14.	Participant N	0.205	3.321‡	0.109
15.	Participant O	-0.115	-1.151	0.183
16.	Participant P	0.309	3.680‡	0.202
17.	Participant Q	0.176	1.376	0.133
18.	Participant R	-0.042	-0.394	-0.110
19.	Participant S	-0.001	-0.016	0.188
20.	Participant T	0.446	3.172‡	0.576
21.	Participant U	-0.121	-1.490	0.168
22.	Participant V	-0.038	-0.318	0.221
23.	Participant X	-0.275	-2.311	0.280

*OLS regressions allowing for MA(1)-error structure. Data as described in section 2. ‡ Rejects for the individual at the α=0.05-overall significance level for six regressions. ‡‡ Rejects for the entire set of regressions at the α=0.05-overall significance level.

TABLE 3E

Tests for Idiosyncratic Bias*

Dependent Variable: Idiosyncratic Error ($err_i - err_{ave}$)

	Regression	Constant	t for H_0: $\delta=0$	MA(1)
	One-Q-Ahead Second Month			
1.	Participant A	-0.268	-2.843	0.409
2.	Participant B	0.057	1.326	-0.057
3.	Participant C	-0.173	-2.227	0.061
4.	Participant D	-0.065	-0.917	0.189
5.	Participant E	-0.168	-1.815	0.280
6.	Participant F	-0.039	-1.108	-0.283
7.	Participant G	-0.310	-2.228	0.327
8.	Participant H	-0.056	-1.249	-0.480
9.	Participant I	0.413	1.907	0.260
10.	Participant J	-0.257	-1.817	0.496
11.	Participant K	0.001	0.014	0.529
12.	Participant L	0.237	3.889‡	-0.094
13.	Participant M	-0.124	-0.864	0.192
14.	Participant N	0.170	3.174‡	-0.062
15.	Participant O	-0.062	-1.225	-0.148
16.	Participant P	0.202	2.098	0.516
17.	Participant Q	0.066	0.405	0.719
18.	Participant R	0.119	3.039‡	-0.149
19.	Participant S	-0.008	-0.132	-0.071
20.	Participant T	0.472	2.741	0.385
21.	Participant U	-0.001	0.001	0.140
22.	Participant V	-0.065	-0.653	0.053
23.	Participant X	-0.164	-1.230	0.414

*OLS regressions allowing for MA(1)-error structure. Data as described in section 2. ‡ Rejects for the individual at the α=0.05-overall significance level for six regressions. ‡‡ Rejects for the entire set of regressions at the α=0.05-overall significance level.

TABLE 3F

Tests for Idiosyncratic Bias*

Dependent Variable: Idiosyncratic Error $(err_i - err_{ave})$

	Regression	Constant	t for H_0: $\delta=0$	MA-Parameter
	One-Q-Ahead Third Month			
1.	Participant A	-0.165	-1.739	0.440
2.	Participant B	0.008	0.158	0.396
3.	Participant C	-0.082	-1.254	-0.006
4.	Participant D	-0.037	-0.853	-0.114
5.	Participant E	-0.037	-0.325	0.531
7.	Participant G	-0.220	-2.132	0.228
8.	Participant H	-0.024	-0.339	-0.090
9.	Participant I	0.141	0.855	0.213
10.	Participant J	-0.088	-0.818	0.573
11.	Participant K	-0.057	-0.961	0.386
12.	Participant L	0.243	3.102‡	0.092
13.	Participant M	0.147	1.457	0.007
14.	Participant N	0.138	2.436	0.266
15.	Participant O	-0.005	-0.504	0.606
16.	Participant P	0.187	2.521	0.323
17.	Participant Q	0.121	0.961	0.259
18.	Participant R	0.014	0.316	0.115
19.	Participant S	-0.072	-1.307	0.074
20.	Participant T	0.273	3.151‡	-0.185
21.	Participant U	-0.098	-4.846‡‡	-0.367
22.	Participant V	-0.081	-1.635	-0.033
23.	Participant X	-0.193	-2.088	0.138

*OLS regressions allowing for MA(1)-error structure. Data as described in section 2. ‡ Rejects for the individual at the $\alpha=0.05$-overall significance level for six regressions. ‡‡ Rejects for the entire set of regressions at the $\alpha=0.05$-overall significance level.

TABLE 4A

Tests for Efficiency using Past Average Forecast*

Dependent Variable: Forecast Error ($\text{Outcome}_t - \text{Forecast}_t$)

	Regression	Constant	Difference Pastave-Fore	Corr
1.	Current Quarter 1st Month	0.022 (0.433)	0.406 (4.268)	0.676
		N=433	R^2=0.22	
2.	Current Quarter 2nd Month	0.029 (1.134)	0.601 (10.92)	0.571
		N=435	R^2=0.46	
3.	Current Quarter 3rd Month	0.013 (1.111)	0.783 (20.50)	0.649
		N=419	R^2=0.77	

*OLS regressions with corrected standard errors. In parentheses t-statistics for the null hypothesis of zero coefficient on constant and difference term. Data as described in section 2.

TABLE 4B

Tests for Efficiency using lagged Past Average Forecast*

Dependent Variable: Forecast Error (Outcome_t-Forecast_t)

	Regression	Constant	Difference Pastave lag - Forecast	Corr
1.	Current Quarter 1st Month	0.019	0.267	0.593
		(0.373)	(2.988)	
		N=433	R^2=0.14	
2.	Current Quarter 2nd Month	0.010	0.260	0.339
		(0.451)	(5.249)	
		N=435	R^2=0.21	
3.	Current Quarter 3rd Month	0.013	0.374	0.328
		(0.954)	(8.279)	
		N=419	R^2=0.39	

* OLS regressions with corrected standard errors. In parentheses t-statistics for the null hypothesis of zero coefficient on constant and difference term. Data as described in section 2.

TABLE 5

Tests for Extrapolation*

Dependent Variable: Forecasted Change ($Forecast_t$-$Outcome_{t-1}$)

	Regression	Constant	Past Change in Outcome	Corr
1.	Current Quarter 1st Month's Forecasted Change	-0.045 (-0.666) N=433	0.561 (4.590) R^2=0.39	0.618
2.	Current Quarter 2nd Month's Forecasted Change	-0.003 (-0.042) N=435	0.615 (4.519) R^2=0.42	0.780
3.	Current Quarter 3rd Month's Forecasted Change	-0.097 (-0.896) N=440	0.438 (2.230) R^2=0.17	0.909

*OLS regressions with corrected standard errors. In parentheses t-statistics for the null hypothesis of zero coefficient on constant and change term. Data as described in section 2.

Table 6A-C

Tests for Efficiency*

Dependent Variable: Forecasted Change ($Forecast_{t.3}$-$Outcome_t$)

Regression	Constant	Past Change in Monthly Outcome	Corr
Current Quarter 3rd Month's Forecasted Change on ($out_{t.2}$-$out_{t.1}$)	-0.007 (-0.792) N=419	0.095 (2.568) R^2=0.025	0.050

Tests for Efficiency*

Dependent Variable: Forecasted Change ($Forecast_{t.2}$-$Outcome_t$)

Regression	Constant	Past Change in Monthly Outcome	Corr
Current Quarter 2nd Month's Forecasted Change on ($out_{t.t}$-$out_{t-1.3}$)	-0.022 (-1.054) N=435	-0.086 (-1.001) R^2=0.01	0.17

Tests for Efficiency*

Dependent Variable: Forecasted Change ($Forecast_{t.1}$-$Outcome_t$)

Regression	Constant	Past Change in Monthly Outcome	Corr
Current Quarter 1st Month's Forecasted Change on ($out_{t-1.3}$ $out_{t-1.2}$)	-0.041 (-0.941) N=433	0.108 (0.718) R^2=0.001	0.415

* OLS regression with corrected standard errors. In parentheses t-statistics for the null hypothesis of zero coefficients for the constant and the change term. Data as described in section 2. The notion t.i means quarter t, ith month.

TABLE 7

Tests for Efficiency using the Past Spread*

Dependent Variable: Forecast Error ($\text{Outcome}_t - \text{Forecast}_t$)

	Regression	Constant	Past-Quarter Spread	Corr
1.	Current Quarter 1st Month	0.016 (0.292)	0.231 (0.788)	0.412
		N=433	R^2=0.01	
2.	Current Quarter 2nd Month	0.012 (0.454)	0.037 (0.270)	0.182
		N=435	R^2=0.01	
3.	Current Quarter 3rd Month	0.001 (0.018)	0.052 (0.659)	0.098
		N=440	R^2=0.01	

*OLS regressions with corrected standard errors. In parentheses t-statistics for the null hypothesis of zero coefficient on constant and spread term. Data as described in section 2.

TABLE 8

Tests for Efficiency using own Price Forecasts*

Dependent Variable: Idiosyncratic Forecast ($Fore_t - Foreave_t$)

	Regression	Constant	Idiosyncratic Price Fore	Corr
1.	Current Quarter 1st Month	-0.001	0.019	-0.033
		(-0.104)	(1.284)	
		N=429	R^2=0.01	
2.	Current Quarter 2nd Month	-0.001	0.024	-0.033
		(-0.038)	(1.609)	
		N=432	R^2=0.01	
3.	Current Quarter 3rd Month	-0.001	-0.004	-0.022
		(-0.074)	(-0.537)	
		N=433	R^2=0.01	

* OLS regressions with corrected standard errors. In parentheses t-statistics for the null hypothesis of zero coefficient on constant and idiosyncratic price forecast term. Data as described in section 2.

TABLE 9

Tests for Efficiency using own Changes in Forecasts*

Dependent Variable: Forecast Error (outcome-forecast)

	Regression	Constant	Change in Forecast	Corr
1.	Current Quarter 3rd Month's Error on Change (3rd minus 1st month)	0.006 (0.523) N=384	-0.127 (-4.470) R^2=0.08	0.099
2.	Current Quarter 2nd Month's Error on Change (2nd minus 1st month)	0.022 (1.050) N=396	-0.230 (-4.845) R^2=0.095	0.220
3.	Current Quarter 3rd Month's Error on Change (3rd minus 2nd month)	0.004 (0.414) N=385	-0.236 (-6.134) R^2=0.13	0.102

*OLS regressions with corrected standard errors. In parentheses, t-statistics for the null hypothesis of zero coefficient on constant and change term. Data as described in section 2.

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